Route Following Without Scanning

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Abstract. *Desert ants are expert navigators, foraging over large distances using visually guided routes. Recent models of route following can reproduce aspects of route guidance, yet the underlying motor patterns do not reflect those of foraging ants. Specifically, these models select the direction of movement by rotating to find the most familiar view. Yet scanning patterns are only occasionally observed in ants. We propose a novel route following strategy inspired by klinokinesis. By using familiarity of the view to modulate the magnitude of alternating left and right turns, and the size of forward steps, this strategy is able to continually correct the heading of a simulated ant to maintain its course along a route. Route following by klinokinesis and visual compass are evaluated against real ant routes in a simulation study and on a mobile robot in the real ant habitat. We report that in unfamiliar surroundings the proposed method can also generate ant-like scanning behaviours.*

Keywords: navigation; ant; robot; route following; klinokinesis

1 Introduction

Desert ants are impressive insect navigators, foraging over large distances (sometimes 100s of metres) in extremely hostile environments without the use of pheromone trails. Instead, desert ants navigate through their environment using primarily visual cues [1]. This capability is all the more impressive when one considers the the ant's relatively small brain and their low resolution eyes (in the order of 4° angular acuity). As such they have become a model system for bio-roboticists seeking computationally efficient strategies for navigation in natural environments. One specific behaviour will be the focus of this paper; visual route following [2,3] (see figure 3 for an example ant route).

Recently a new family of visual navigation models have been shown sufficient to recreate route following in simulated environments with characteristics similar to those of real ants [4,5]. Fundamental to the success of these algorithms is a methodology termed the "visual compass"; first described by Zeil et al [6]. The visual compass relies on the observation that any stored image inherently encodes information about the viewing direction from which it was taken. Hence, it is possible to later recover that direction by simply rotating on the spot until the best match is found between the current view and the visual memory [6] (see Fig.

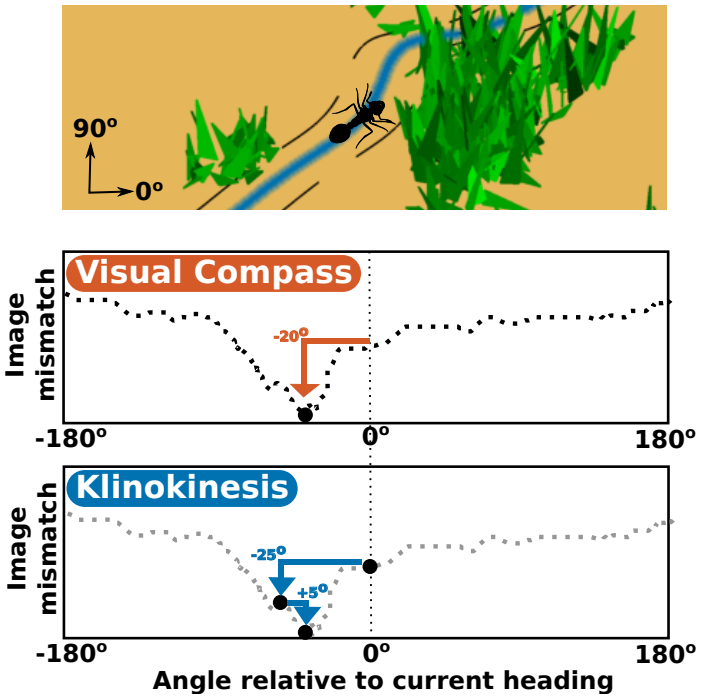

Fig. 1. *Route following using the rotational image difference.* The top panel shows the scenario of an ant coming to a 20° left bend in its route (ant moving from lower left to top right along the blue line). The central panel shows the full rotational image difference function (rIDF) that is generated using a scan. rIDFs are characterised by a minimum where current and stored views match, flanked by increasing values of image mismatch [6]. By moving in the direction giving the best match (in this case -20° the ant will progress along it's route. The bottom panel shows how a klinokinesis method might work by modulating a turn using only the image mismatch between the current view and all route memories. As the ant heading has deviated from the route a corrective turn is made (in this case -25°. The alternating turns allow the minima to be continually optimised as shown by the second, smaller +5° turn.

1). This principle can be extended to a bank of memories sampled densely across a previously travelled path. By looking for the best match across all memories, the direction of the travel at any particular route position can be recovered. If this process is repeated at each step, it is sufficient to retrace a previously travelled path [4,5].

Yet, a crucial discrepancy remains between these models and observations of real ants. Specifically, while ants have been observed rotating on the spot before selecting a direction of travel (in a behaviour termed 'scanning') [7], consistent with aligning their current visual input with their memory, this behaviour is only expressed in specific circumstances (e.g. when an ant is released in an unfamiliar environment). Under normal conditions ants travelling along a familiar route

scan infrequently, if at all [7]. This suggests that ants might use an alternative strategy to maintain their progress along the route.

In this work we present a novel method by which ants might continuously correct their heading along a learned route without the need to repeatedly scan the environment. Inspiration comes from the klinotaxis and klinokinesis behaviours observed in Drosophila larvae [8] and bacteria [9]. These animals can approach a favourable odour by directing turns relative to two temporally and spatially distinct sensor readings (klinotaxis) or through a simpler undirected strategy by increasing the frequency of turns relative to the sensory input (klinokinesis) [9]. The algorithm described in this work is most similar to klinokinesis given the absence of direct comparison between paired sensory readings. However rather than modulating the likelihood of initiating a turn, the sensory input (in this case the instantaneous image-difference between current view and route memories) modulates the size of alternating left and right turns and also forward step size (or speed). This schema essentially sub-samples the rotational image difference function and exploits its characteristic shape to correct for deviations in orientations along a previously travelled path (see Fig. 1). We show that this simple sensory-motor routine is capable of route following in a simulated ant world and on a custom wheeled robot in the ant habitat. Further, in specific scenarios this algorithm can generate "scan-like" behaviours and we thus propose that scans may be an emergent property of a simpler route following strategy.

2 Methods

2.1 Navigation Algorithms

Two approaches to route following were implemented and tested on a robot and in a simulation environment: visual compass and klinokinesis. The memory bank for both models was identical: comprising densely sampled images (every 1cm for simulation, and every 10cm for the robot) facing along the route to be retraced. Both algorithms use the sum squared per-pixel difference of two grayscale images as a measure of difference between them:

$$SSD(I_1, I_2) = \log \sum_i (I_1(i) - I_2(i))^2 \tag{1}$$

where I_1 and I_2 are images and i is the index of corresponding pixels within both images. The logarithm of the image difference was used to lineralise the SSD which is proportional to the turn angle and step size of the klinokinesis algorithm.

Visual compass The visual compass algorithm works by measuring the difference between the current view as the agent rotates, and all views comprising the route memory (see Fig. 1 central panel). The orientation of the agent when the minimum image difference is observed is chosen as the direction of travel:

$$Best\ Direction = \arg\min_{r} SSD(M(x), C(r)) for\ all\ x \tag{2}$$

where M is the bank of images making up the route memory and x is index of each memory; C is the current image taken as the agent rotates through r°İn our case we limited scanning to +/-60°around the current heading in 2° steps for the virtual environment and in approximately 12° steps for robot.

Klinokinesis Our Klinokinesis-like algorithm works by alternately turning left and right between forward steps. The magnitude of each turn is modulated by the size of the minimum image difference between the current view and all route memories. Thus, while on the route and facing in the correct direction a low image difference would be computed and the agent will turn very little. But when the route bends, and the view mismatch increases, the agent will perform a larger turn. If this turn happens to be in the correct direction a familiar view will be restored, and the agent will recover the path and make a smaller subsequent turn. If, the first turn happens to be away from the route, the view mismatch should increase further so a larger corrective turn in the opposite direction will be implemented and the route recovered (see Fig. 1 lower panel).

At each step, the unfamiliarity is computed as described for the visual compass method above:

$$Unfamiliarity = \min_{x} SSD(M(x), C) \tag{3}$$

M, C and x follow the convention defined above.

We then normalize unfamiliarity to be between 0 and 1:

$$Normalized\ unfamiliarity = Unfamiliarity / Unfamiliarity_{max} \tag{4}$$

where $Unfamiliarity_{max}$ is the biggest image difference between the first training image and the rest of the training images:

$$Unfamiliarity_{max} = \max_{x} SSD(M(1), M(x)) \tag{5}$$

In our method the turn angle is given by:

$$Turn\ angle = \alpha * Normalized\ unfamiliarity \tag{6}$$

α is the scaling factor which is optimised for route following (described below).

We also scale the forward step size between turns. This allows the agent to take larger steps when the view is very well matched (i.e. on the route), but reduce step size (or slow down) when the mismatch increases, before the route is lost completely. The step size is modulated by the image difference value as shown in equation 7 where β is the scaling parameter.

$$stepsize = (1 - Normalized\ unfamiliarity) * \beta \tag{7}$$

Parameter Tuning For simulation tests, we performed a parameter sweep for α and β, in the range 60° to 160° in 20° steps for max turn angle α and 0.5cm to 3.5cm in 0.5cm steps for max step size β. We selected the parameters that resulted in the smallest median number of route following errors over the 15 routes (see 2.3 for definition of error).

2.2 Robot Study

We first assessed the performance of both navigation methods in a robot study in the real ant habitat, as a proof of principle.

Hardware configuration The main hardware component of the robot is an Android device (Nexus 5 smartphone), providing an easy to program system supported by dual integrated cameras, a powerful processor (2.26Ghz quad-core; 2Gb RAM; 32Gb of internal storage), 2300mAh battery, and numerous connectivity and sensor options (e.g. GPS, accelerometers) [10]. A panoramic mirror (Kogeto Dot) was attached to the front facing camera giving unobscured 360° vision, only 8cm from the ground. The drive unit is a Pololu Zumo Robot base, providing a small yet semi-rugged, self-powered, platform on which to mount the main device. An Arduino Uno relays motor and sensory commands from base to android device and vice versa via a USB On-The-Go (OTG) cable. A complete guide to constructing the roboant Edinburgh (see Fig. 2) is provided at our blog (`https://blog.inf.ed.ac.uk/insectrobotics/roboant/`).

Software A stand-alone app was written implementing both visual compass and klinokinesis algorithms described above. Grayscale panoramic images were sampled using the front facing camera with panoramic lens, before being normalised using OpenCV (adaptive histogram normalisation) and downsampled to approximate ant-eye resolution of 1200 pixels. Example Roboant videos: full resolution `http://youtu.be/W9K1G3XiSAg` and downsampled `http://youtu.be/jWCk40O8jWg`.

The entire software project has been made available as an open source package `https://github.com/d3kod/roboant` and the navigation algorithm are available as a downloadable plug-and-play package app on the Google Play Store `https://play.google.com/store/apps/details?id=uk.co.ed.insectlab.ant`.

Robot Trials The robotic pilot study was conducted at our current ant field site on the outskirts of Sevilla, Spain, between 18th and 22nd June, 2014. A test track 8m long (similar in length to ant routes in simulation) was constructed using laminated wooden boards which provide a base on which the robot could easily move (persistent toppling occurred on the natural terrain). Two training routes were recorded: one turning left at a junction point and the other turning right (see Fig. 2C); thereby ensuring that any positive route recapitulations were not simply a consequence of an environmental bias. To assess the ability

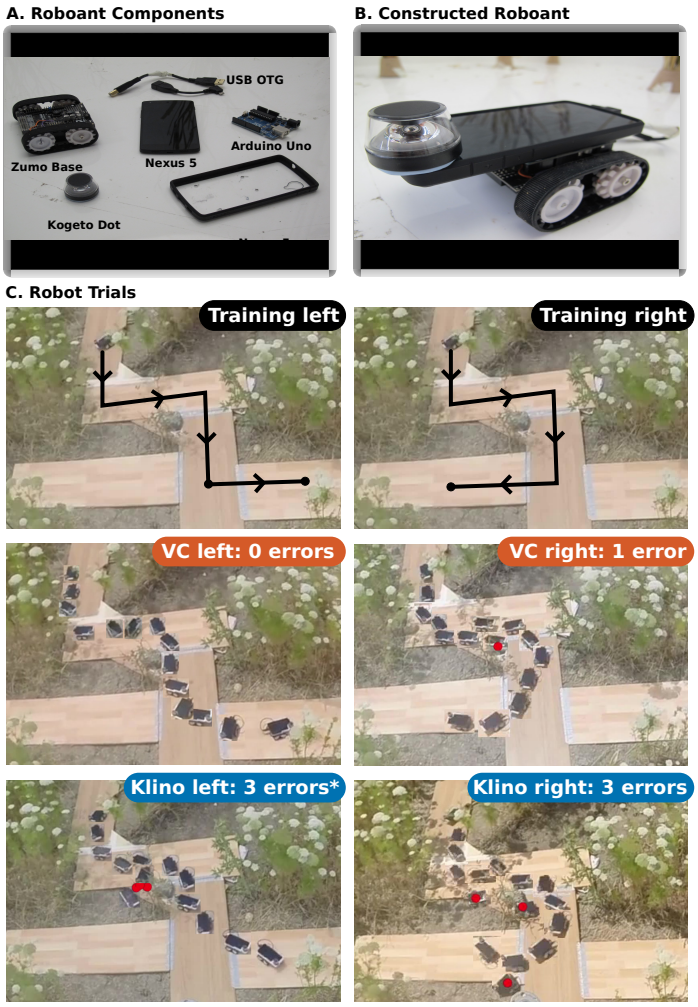

Fig. 2. *Robot route following in the real ant habitat. A.* The off-the-shelf components which make up Roboant are shown prior to assembly. *B.* The completed robot being tested in the lab. *C.* Robot trials at our field site in Seville, Spain. Training images were sampled making either a left turn (top left panel) or right turn (top right panel) at the junction point. The paths taken by the robot in each condition and when driven by both algorithms (VC: visual compass, Klino: klinokinesis) are shown using still frames captured from an overhead camera (GoPro 3) mounted on a pole. *Note that all errors for the klinokinesis on the left trial were clustered at the same location.

of the methods to retrace the learned path we recorded the instances when the robot path deviated more than 20cm from the route (in this case when it fell off the track), whether each method managed to make the correct turn at the crossroads, and also the total time taken to complete each route.

2.3 Simulation Study

Given the positive results from the robot trials we then undertook a detailed simulation study allowing full parameter tuning and performance to be compared to several real ant paths.

Real Ant Routes Our training and verification data comes directly from the real routes of 15 ant of the species *Cataglyphis velox* as they travelled to and from an experimental feeder located 7.5m from the nest in their natural habitat of scrub near Seville, Spain [3]. Each ant developed an idiosyncratic route leading it to the food and another unique route leading it home again (see Fig. 3 for example ant route).

3D World Both models were assessed in a corresponding virtual environment of the ant habitat, consisting of a 10x10 metre area in which each tussock is represented as a collection of triangular grass blades of appropriate size and height, with a distribution of shading taken randomly from the intensity range in the panoramic pictures ([11]). Within this virtual environment, we can generate images true to the visual field (296° horizontally, 76°vertically) and resolution (4° [12] of the ant. The 3D world and image creation software are available at `http://www.insectvision.org/`. Images were converted to grayscale using the standard Matlab function (Matworks, Inc).

Simulation Trials Both visual compass and klinokinesis algorithms were supplied with the same route memory database consisting of images sampled every 1cm along the inward routes of 15 ants (route lengths approx 8m each). The performance of the models is again assessed by computing the number of deviations greater than 20cm from the route (more than 20cm from the route the rIDF disappears and all models become lost). The total number of route errors and the number of computations amassed across a route are used to assess performance.

3 Results

3.1 Successful route following by a robot in the real ant habitat

We first tested the visual compass and klinokinesis algorithms on our custom Roboant platform in the real ant environment. The robot faced challenges not experienced in the simulated world. Environmental disturbances such as changing illumination as clouds passed in front of the sun and bushes moving in the wind were present. Furthermore, the robot base had no means of accurately measuring its heading angle or distance travelled and as such relied on timing of the duration of the motor signal which proved extremely variable in tests.

Both visual compass and klinokinesis methods succeeded in retracing the stored routes, and in both cases made the correct turns at the junction point

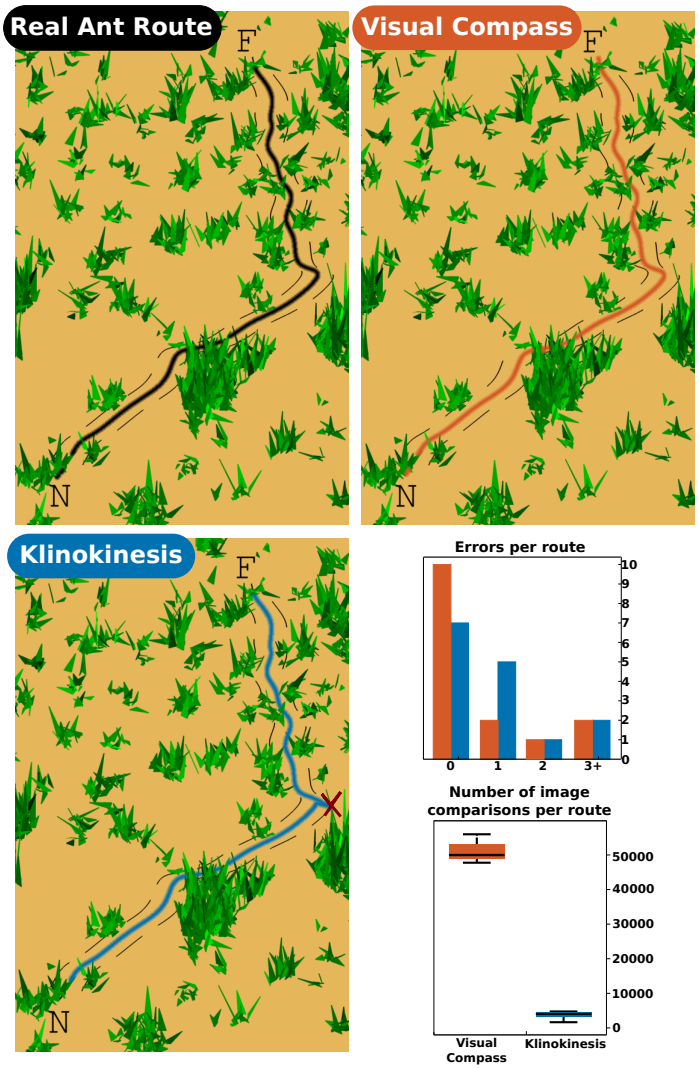

Fig. 3. *Visual compass vs klinokinesis in 3D environment. Top Left Panel.* Example of the real ant path, plotted in our 3D world. The feeder location (start of the route) is labelled F, and the nest (end of the route) marked N. *Top Right & Bottom Left Panels.* Example routes using the visual compass and klinokinesis algorithms when trained with images sampled along real ant route route shown. The black spaced line indicates the boundary 20cm from the route where an error would be generated. An example of an error is shown for the klinokinesis homing by the red cross. *Bottom Right Panel* The number of errors produced across all 15 routes (top), and the number of image comparisons required to those complete simulations (bottom) are shown for both visual compass and klinokinesis algorithms (red and blue boxes respectively).

(see Fig. 2(c-f)). The visual compass algorithm produced only 1 error in total whereas the klinokinesis algorithm accumulated 6 errors (4 if the cluster of errors for the left route are counted as one). This pilot study offers compelling evidence that route following by klinokinesis of the rIDF is possible. Additional benefits of bypassing full scans is also clear from the times taken to complete trials (visual compass: 285s and 375s; klinokinesis: 225s and 190s). The speed up is a modest 63% when comparing the entire time taken to complete the trial, however we note that much of that time was spent by the experimenter emerging from his hidden location before finding the stricken robot and returning it to the route. We expect both a reduction in errors and further speed up when the robot base is fitted with more accurate distance and turning measurement (e.g. wheel encoders).

3.2 Klinokinesis produces accurate and rapid route following in simulation

Following the success of the route following algorithms on the robot we analysed performance of the models further in our simulation, verifying results against real ant routes in an accurate 3D simulation of their environment. Fig. 3 shows an example of the positive route following performance of both visual compass and klinokinesis algorithms. The consistency across the 15 different routes tested are shown in the low number of route deviations reported in the for both models (Fig. 3 bottom right). The klinokinesis method thus appears as effective as full scanning for retracing a previously travelled path.

Klinokinesis significantly outperforms the visual compass in computational workload as shown in Fig. 3 lower right. The median number of image comparisons required by the visual compass algorithm to complete a route is 49980 (IQR=4065) whereas the klinokinesis algorithm requires only 4039 comparisons (IQR=117). This 10-fold reduction in computational load allows routes to be traversed in a fraction of the time required by previous models.

We note that best performance of the klinokinesis algorithm was found for a max turning angle of 80° and max stepsize of 3cm.

4 Discussion

Recently models of route following in ants have concentrated on how ants might use visual cues alone to navigate long range paths [4,5]. While these methods can generate ant-like routes through complex environments, the underlying behaviour (i.e. scanning) does not fit with real ant data [7]. In this work we implemented a novel route following strategy inspired by klinokinesis, as used by Drosophila larvae and bacteria to ascend odour gradients [8,9]. By modulating the size of alternating turns and forward step size in proportion to the instantaneous image difference between current and stored views our algorithm descends the rotational image gradient, and thus maintains heading alignment with a previously travelled path.

We firstly probed the ability of a klinokinesis-like algorithm to perform route guidance on a wheeled robot in the ant's natural environment. Both klinokinesis and visual compass strategies were shown to be capable of at least partial route following along an 8m. In all cases the models followed the training route correctly when faced with a choice of directions. The positive outcome of the pilot study is all the more impressive given the low resolution visual input (approx 1200 pixels) and environmental factors including movement of vegetation by wind and dynamic lighting.

A subsequent simulation study validated models more rigorously by comparing performance against 15 real ant routes in our 3D reconstruction of an ant habitat. The klinokinesis algorithm produced similar error scores as the visual compass methodology but used only 8% of the total number of image comparisons resulting in a marked improvement in speed in both robot and simulation trials. Further, the paths produced by the algorithm show a natural zig-zag pattern, which closely matches the fine-scale movement patterns reported in homing ants which are sinusoidal rather than straight [13,14,15].

The positive results of both simulation and robot studies support the plausibility of the use of a klinokinesis-like mechanism by ants and also provides inspiration for a computationally cheap visual route following strategy for use on mobile robots. There are a number of immediate amendments that could be made to improve the performance of the robot. Firstly, applying rigorous parameter tuning methods (e.g. allowing non-linear weighting and on the robot itself) to optimise turn angle and step size, coupled with improved turn and speed measurements (e.g, by adding wheel encoders) would immediately improve robot performance. Further improvements might be possible by modulating turns not by the instantaneous image difference but by the change in image difference, giving a natural normalisation in readings and the ability to invert the turn direction (e.g. when the change in sensory input becomes negative). We note that an amendment to the algorithm would change the underlying mechanism from a klinokinesis-like to a klinotaxis-like behaviour. Similar klinotaxis inspired methods have recently been implemented in both simulation and robot studies to ascend light gradients [16].

Finally, we report on an interesting behaviour that emerged during both studies. During robot trials, when the robot path diverged from the route, it would start to perform large turns that were exaggerated by its rotational momentum. As the forward step size would be small this behaviour looked very similar to ant scans (see Fig. 4a), and in some cases allowed the robot to recover the route. We occasionally observed similar results during parameter tuning in our simulation study, whereby our simulated ant performed a series of large turns before aligning itself with the route. It is possible to trigger such behaviours by placing the simulation ant at specific locations on the route but at the wrong heading, with parameters settings that allowed large turns (see Fig. 4b). We thus suggest that scanning may be an emergent property of a simpler route following strategy, rather than a fundamental behavioural routine required for route following.

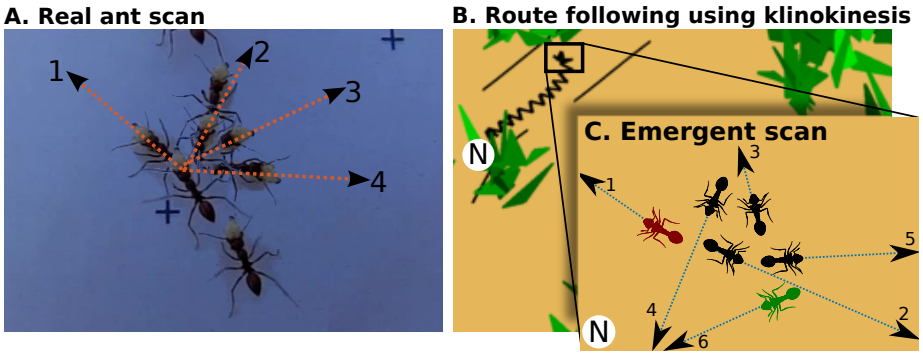

Fig. 4. *Emergent scans. A* Example of an ant scan. Frames in which the ant has paused are overlaid, showing 4 distinct viewing directions (labelled arrows) before a direction of movement was selected. Video adapted from [7] with permission. *B* The motions resulting from klinokinetic homing when the virtual ant is placed on the route but with the wrong heading (red ant, with direction shown by arrow 1). Note, the nest direction to the lower left labelled N. Shown are the 5 subsequent movements of the simulated ant before finally moving towards the nest (green ant, with direction shown by arrow 6). Note that the parameters used are larger than those optimized for homing - $\alpha = 8$ and $\beta = 600$.

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